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Research Paper

Optimal Shaping of Non-Conventional Permanent Magnet Geometries for Synchronous Motors via Surrogate Modeling and Multi-Objective Optimization Approach

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Abstract: A methodology is proposed for optimal shaping of permanent magnets with non-conventional and complex geometries, used in synchronous motors. The algorithm includes artificial neural network-based surrogate model and multi-objective search based optimization method that will lead to Pareto front solutions. An interior permanent magnet topology with crescent-shaped magnets is also introduced as the case study, on which the proposed optimal shaping methodology is applied. Produced torque per magnets mass and percentage torque ripple are considered as the objectives, in order to take both performance and cost into account. Multi-layer perceptron architecture used to create the approximated model is trained to fit the samples collected via time-stepping finite element simulations. The methodology can be easily generalized to offer a fast and accurate method to optimally define arbitrary permanent magnet shape parameters in various synchronous motors.

1 Introduction

PERMANENT magnet motors are used widely for commercial electric and hybrid electric vehicles [1, 2]. These motors are known mostly for their high efficiency and high torque capability characteristics. Recently, several researches have been conducted in order to achieve an optimum design of Permanent Magnet Synchronous Motors (PMSMs) using various approaches. A typical design optimization method can be characterized based on its two principle phases: (1) the modeling procedure and (2) the searching fashion to find the best design solution.

To deal with design problems, one can find various modeling methods for electrical machines, which can be categorized in two groups. The first category, which

also can be known as conventional models, includes physic-based methods that try to represent and solve the field equations (i.e., Maxwell equations) in the machine under study. These methods can be analytical (e.g., formal solutions of Maxwell equations in constant permeability regions), semi-analytical (e.g., magnetic equivalent network) or numerical (e.g., Finite Elements Analysis (FEA)) that compromise between the computation cost and the accuracy [3]. Although, the use of these models is essential at the initial design steps, they have been utilized widely at the optimization level, too [4-9]. Whilst, developing an analytical model is subjected to several restrictions, FEA not only can offer the highest accuracy but also can easily represent arbitrary complex geometries. However, using such model within a search based optimization procedure may be too much time consuming and hence practically impossible.

The next category of modeling methods has been developed to overcome the mentioned challenges. This alternative approach, called surrogate modeling methods, consists of mathematical-based models that can be derived using Design of Experiments (DOE) techniques. In order to construct a surrogate model two steps have to be performed: (1) samples collection and

(2) function approximation or fitting [10]. According to the DOE techniques there are several principles to define the samples required to create the dataset, including factor design [11], Latin hypercube design [12, 13], orthogonal design [14, 15], and etc. Next, the fitting process must be done using certain mathematical models, e.g., response surface [16, 17], Kriging model [18, 19], Artificial Neural Networks (ANN) [11, 20], etc.

After developing an appropriate model by trading off between its accuracy and computational cost, the global best design must be searched among the feasible solutions. To this end, intelligent optimization methods (e.g., Genetic Algorithm (GA) and Particle Swarm Optimization (PSO)) have been utilized widely in the recent researches. Design optimization of electrical machines is often a multi-criteria problem, because several characteristics vary in a conflicting manner by changing the design variables. These multi-criteria problems can be represented via either a single-objective problem, as done in [21], or a multi-objective problem. The last one, which has attracted much attention in the recent years, can be solved through different methods such as Pareto approach [20], multi-criteria decision making methods [22], etc.

Permanent Magnets (PMs) design is one of the most important steps of designing the Permanent Magnet Synchronous Motors (PMSMs). Conventionally, simple basis geometries are considered for PMs (e.g., a rectangular shape) in order to simplify the construction process. However, better performance characteristics may be achieved by defining more complex basis geometries [23]. Hence, the problem will be complicated due to the need for developing new models and the necessity for defining more geometrical variables.

In this paper, a new framework is introduced for shape optimization of PMs with non-conventional geometries. The algorithm includes using an ANN as the basis function to create a surrogate model, and employing a multi-objective Pareto optimization method to calculate the best set of possible designs (Pareto solutions) according to the defined objectives. Moreover, the introduced method is applied to an Interior PMSM (IPMSM), the specifications of which are appropriate for small electric vehicle applications. The studied IPMSM has a distributed armature winding and a crescent PM shape, as an example of non-conventional basis geometry. An advantage of the crescent PM shape can be the relatively larger saliency ratio, which can lead to more reluctance torque and better field weakening capability. Also, the produced torque per PMs mass as well as the percent torque ripple are considered as the optimization objectives, so that both the performance and the cost are taken into account. PMs sizing parameters are the only variables of the optimization problem. The paper will go on by a brief representation about the studied IPMSM and the basis

analytical sizing equations, following by the detailed contents about the optimization procedure, including modeling and multi-objective optimization routes, in the third section. Finally, the results will be illustrated in the fourth section along with the required discussions.

2 Analytical Design

A 2-D view of the proposed IPMSM is illustrated in Fig. 1. Analytical models are usually preferred for initial design steps. Hence, a simplified magnetic circuit model is used to specify the initial design. Main dimensions (i.e., stack length and core diameters) as well as the whole stator design will be considered finality, while the PMs design will be optimized at the next part. The sizing procedure of the IPMSM starts with the main dimensions using (1) [24]:

$$D_r^2 L = \frac{P_n}{\eta \pi^2 K_w \sigma_{\tan} n / 60} \tag{1}$$

In (1), D_r and L are rotor diameter and stack length, respectively, which are known as the main dimensions of a radial air gap motor. Also, P_n, η and n are nominal power, efficiency and synchronous base speed (in RPM), respectively. The winding factor (K_w) equals to the distribution factor (full pitch winding is assumed) and the mean value of the rotor tangential Maxwell stress ($\sigma_{\tan}$) can be calculated as a function of the magnetic loading ($\hat{B}_g$) and electrical loading (A):

$$\sigma_{\tan} = \frac{1}{\sqrt{2}} A \hat{B}_g \tag{2}$$

Tangential Maxwell stress that is restricted by the electrical and magnetic limitations produces the torque (T) when acting upon the rotor surface:

$$T = \frac{\sigma_{\tan}}{4} D_r (2\pi D_r L) \tag{3}$$

Stator core detailed parameters such as tooth width and yoke height are defined, so that the desired
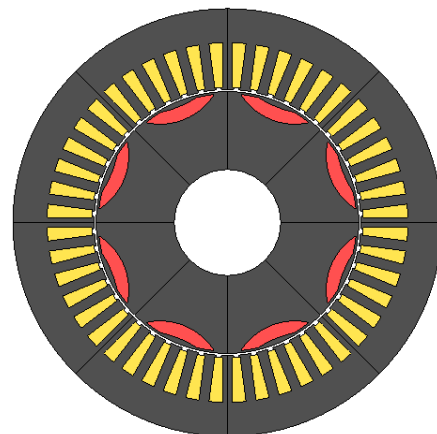

Fig. 1 2-D representation of the studied motor.

magnetic flux density in each part is satisfied. New crescent-shaped PMs with parallel magnetization are adopted in the rotor. Parallel magnetization is usually considered for AC drives rather than the radial pattern, since they can produce more sinusoidal air-gap flux density [25].

Table 1 shows the desired IPMSM specifications for a small electric vehicle such as a scooter.

Certain design of PMs can be achieved by defining four parameters as shown in Fig. 2(a). It was found out that torque ripple can be significantly affected by applying additional gap as depicted in Fig. 2(b). This can be implemented by shifting the PMs through the radial direction, so that the PM volume kept unchanged, although the resultant variation of the mean torque value is strictly non-linear. Therefore, there are five parameters to be determined in order to fulfillment the design of PMs. However the sensitivity levels of the objectives, especially the torque profile, to all

parameters are not the same. Hence, in order to reduce the size of the dataset required for the optimization step, three parameters are selected to which the variation rate of the output torque characteristics is more than the others. It should be noted that this act is done only to reduce the size of calculations, and does not relevance to the optimal design methodology.

3 Optimization Procedure

As mentioned earlier, a multi-objective optimization method combined with a surrogate model of the IPMSM is utilized to calculate the Pareto design solutions. The flowchart shown in Fig .3 describes the sequential procedure.

3.1 Surrogate Modeling Procedure

ANN is used widely for regression applications in different areas of science and engineering. Modeling the behavior of a specific characteristic of an electric motor as a function of several structural variables can also be considered as a regression process. For these applications, ANN parameters (i.e., the values of weights and biases) are calculated mostly via supervised
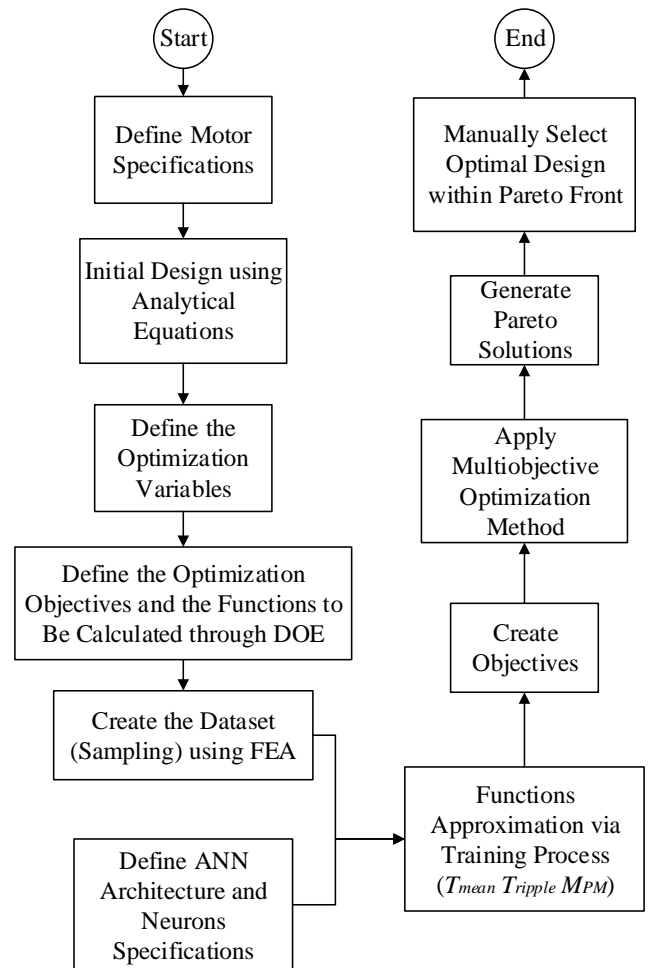
Table 1 Specifications of the studied IPMSM.

Parameter	Value
Base speed [RPM]	3500
Rated power [W]	5000
Rated current [A]	14.8
Pole numbers	8
Stator slot numbers	48

(a)

(b)
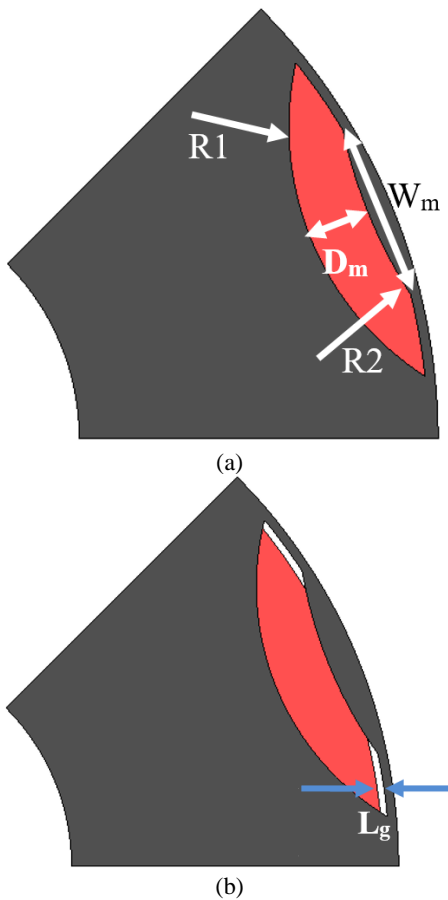
Fig. 2 Crescent PM geometrical parameters to be defined.

Fig. 3 The flowchart of the optimum design using FEA, ANN and NSGA II.

learning methods, in which a proper dataset needs to be prepared. Due to the high achievable accuracy and thanks to the available commercial software packages, FEA can be used to provide the dataset. In other words, FEA have been considered as an excellent valid model that can roughly represent the experiments [11, 20]. In this paper, a full factor approach is used to collect the samples by 2-D time-stepping FEA, where the three optimization variables are discretized within their permitted values (as shown in Table 2) and 847 samples are collected. The parameters R1 and R2 are fixed at 30mm and 50mm, respectively. Three Multi-Layer Perceptron (MLP) ANNs are used to approximate the variations of three functions: mean torque (T_{mean}), torque ripple ($T_{ripple}\%$) and PMs mass (M_{PM}), separately. All networks are formed by one input layer, two hidden layers and one output layer, while the number of neurons of the hidden layers is determined differently for each network, depending on the behavior of the corresponding function. Indeed, the size of the ANN parameters (i.e., number of layers and neurons) is determined via trial and error attempts. Linear function is used as the activation function of the output layer, while hyperbolic tangent is defined for hidden layers. Fig. 4 illustrates the ANNs architecture and the mathematical relationship between optimization variables and network output is presented in (4).

$$Y = \sum_{i=1}^{N_2} \left[W_i \left(\tanh \left(b_i + \sum_{j=1}^{N_1} W_{ji} \left(\tanh \left(b_j + \sum_{p=1}^{3} W_{pj} \times U_p \right) \right) \right) \right) \right] \quad (4)$$

where *U*, *W*, *b* and *Y* are inputs, weights, biases and outputs, respectively. Also, N_1 and N_2 indicate number of neurons in first and second hidden layers.

Table 2 Three optimization design variables and the corresponding range of permitted values.

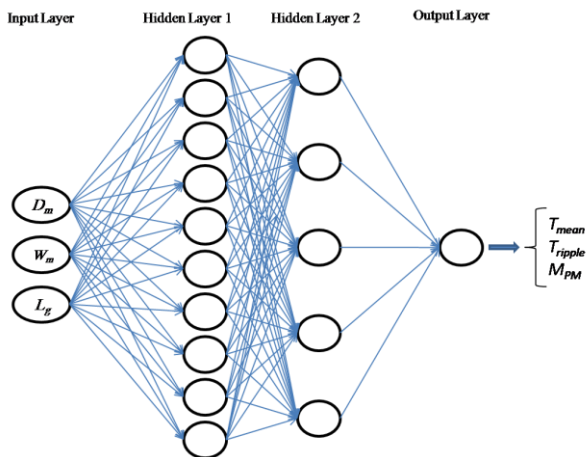| Parameter	Minimum [mm]	Maximum [mm]
D_m	6	7
W_m	15	25
L_g	0	1.5

Fig. 4 MLP NN architecture used as the basis function of the approximated model.

3.2 Multi-Objective Optimization

As mentioned previously, the optimization design of electrical machines is usually a multi-objective task, since the objective functions to be optimized are often in conflict with each other. Among various existing multi-objective optimization approaches, which are surveyed in [26], Pareto method is used widely, since it can provide a set of optimal solutions in which all the objective functions are considered with the same significance. Hence, the designer is able to pick the final design within the set of "best solutions" considering the desired criteria.

To start the optimization process, first, the optimization problem should be properly expressed. In this study, the optimization problem can be formulated as:

$$\text{Max} \quad T_{mean}([X]) / M_{PM}([X]) \quad \&$$
$$\text{Min} \quad T_{ripple}\%$$
$$[X] = [D_m, W_m, L_g] \quad (5)$$

where

$$T_{ripple}\% = \frac{T_{max} - T_{min}}{T_{mean}} \times 100 \quad (6)$$

It can see that two objective functions are assumed. Next, the variables domain (see Table 2) must be searched to find the optimal schemes. To this task, the Pareto approach can be applied within the intelligent optimization methods. Among different Pareto-based intelligent optimization methods, the Non-dominated Sorting GA (NSGA II) is utilized in this paper. Some detailed parameters of the applied NSGA II are presented in Table 3.

4 Results

Applying the simple sizing procedure results in a preliminary design, the characteristics of which are shown in Table 4. The nominal phase Electro-Motive Force (EMF) is considered to be 120V. As mentioned, 847 samples are collected via 2D- FEA, where only one pole partial model can be calculated due to the existing symmetry (as shown in Fig. 5) that leads to considerable computation cost reduction.

Optimization process starts with training three MLP ANNs to approximately modeling three characteristic

Table 3 Detailed parameters of the applied NSGA II.

NSGA II parameters	Value/Type
Population size	100
Selection type	Tournament
Crossover type	Single point
Mutation type	Uniform
Distance measure type	Crowding distance

functions T_{mean}, T_{ripple}, M_{PM}. 95 percent of the dataset are selected randomly, to train the network and the rest of the samples are used to evaluate the network performance. Fig. 6 shows the results of training and testing three networks. The Mean-Squared Error (MSE) criterion is employed to verify the constructed models. As can be seen the best fitting is obtained for MPM function, while T_{ripple} function is modeled with larger MSE, for both train and test levels. This can be justified by the existing difference in the behavior of three characteristics, where the T_{ripple} variations have the most complexity.

The objectives introduced in (5) can be created by combining the networks output. Applying the NSGA II will lead to the set of the best non-dominated solutions. Fig. 7 illustrates the obtained Pareto front.

Usually, the final design is selected manually within the Pareto set by the experts. Here, a typical design is selected as depicted in Fig. 7 to evaluate the design process. The value of three variables corresponding to the selected solution are $D_m = 6.42$mm, $W_m = 17.57$mm and $L_g = 0.37$mm, respectively. Table 5 compares the resulted and predicted values of T_{mean}, T_{ripple} and T_{mean}/M_{PM} calculated by FEA software package and ANNs, respectively, to demonstrate the validity of the optimization procedure. Moreover, the produced torque waveform and induced phase voltage of the final design are shown in Fig. 8.

Table 4 Constant design parameters.

Parameter	Value [mm]
Stator outer diameter	200
Stack length	74
Air-gap length	1
Shaft diameter	50
R1	30
R2	50

(a)   (b)
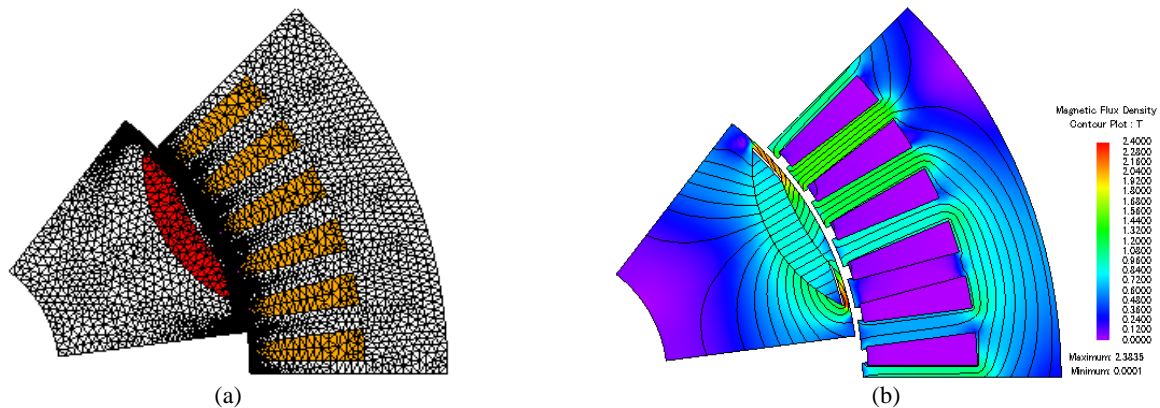
Fig. 5 Partial geometry FE modeling to save the computation time and memory. a) Calculated mesh and b) Magnetic flux density distribution are illustrated for a typical sample.
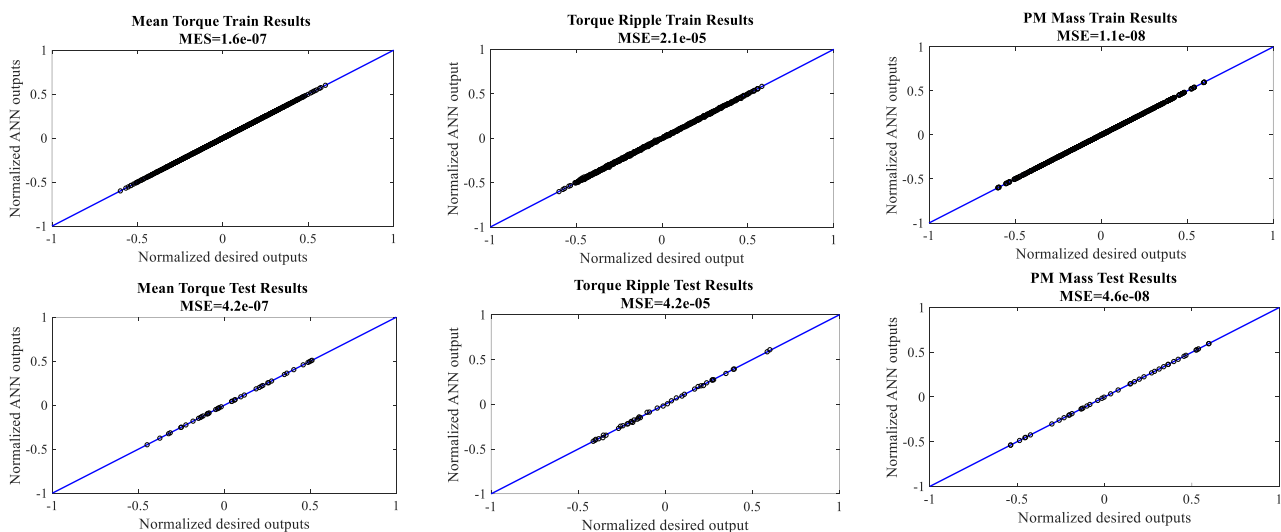

Fig. 6 Training and testing results of three networks, evaluated by MSE criterion, for "Train" and "Test" sets.
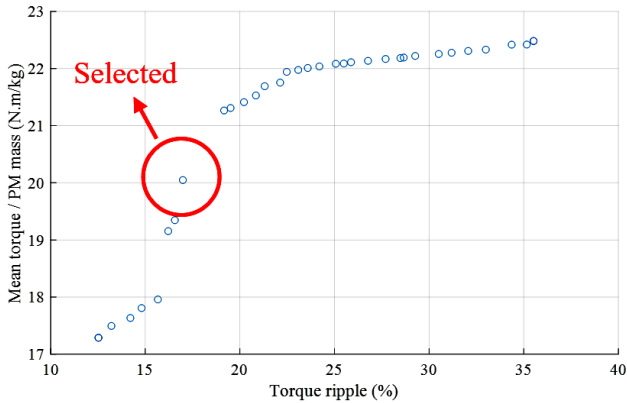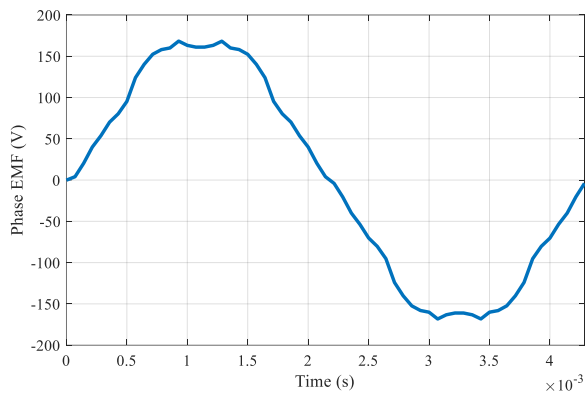
Selected

Fig. 7 Calculated Pareto front.

Table 5 Comparison of the predicted values (via ANN) and computed values (FEA) of the optimized design

Characteristic	Predicted by surrogate model	Resulted from FEA
Mean torque [N.m]	14.68	14.67
Torque ripple [%]	16.99	17.1 %
Torque/PM mass [N.m/kg]	20.04	20.0245

(a)

(b)

Fig. 8 a) Phase EMF and b) produced torque of the optimum design.

5 Conclusions

A new PM shaping algorithm was proposed, which can be easily adopted to optimally calculate the geometrical parameters of various PM shapes in synchronous motors. More complicated PM geometries can result in better motor performances; if proper basis geometry is define. In this paper, crescent-basis geometry is introduced only to show the proposed shaping methodology. The algorithm also leads to a set of Pareto optimal designs. Provided that a proper set of samples are collected, the approximated model can present a competitive accuracy to FE model, while it is significantly superior in term of computation speed, which is exactly an important issue in search based optimizations. Future works could extend to investigate other types of ANN architectures and intelligent optimization methods.

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